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Research Application Summary

Managing cellular network signaling traffic using helper nodes

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Abstract

There is a tremendous uptake of smartphones and other mobile devices that has made mobile apps more popular. Many of these mobile apps are network enabled and can transfer or receive data to/from the network through the signaling process. Mobile and cellular networks are experiencing increased signaling traffic majorly caused by apps running on mobile devices attached to these networks. The signaling traffic is outpacing mobile data traffic by 30-50% and if not handled appropriately, it can have adverse effects on the cellular networks by straining them. Also, the excessive signaling can flood the network causing congestion that may render the network unavailable, or even make it open and vulnerable to attacks. Consequently, operators are forced to deal with the susceptibility of network outages resulting from the excessive signaling. Even though attempts have been made by the industry players to either reduce or handle the volume of signaling traffic, the problem still persists and is growing as more data-enabled mobile devices are released into the market. In this paper, we propose the helper node concept; a device in the Middle Model (DMM) to reduce the signaling traffic volume reaching cellular networks. The model uses helper nodes to service less critical traffic based on classification by network operators. The simulation results for the DMM model show that through the helper nodes servicing other nodes in the network and acting in the relay process, the eventual volume of traffic reaching the core networks is reduced. This model is cost effective in terms of implementation as opposed to introducing new radio network transceivers. However, continuous optimization of cellular network is recommended among other strategies to constantly monitor the volume of signaling traffic in cellular networks.

Key words: Cellular networks, modeling, smartphones, signaling, signal relay

Résumé

L'utilisation amplifiée des smartphones et autres appareils mobiles a permis une popularisation des applications mobiles. La plupart de ces applications mobiles sont activées à partir d'un réseau et peuvent transférer ou recevoir des données vers/depuis le réseau via le processus de signalisation. Les réseaux mobiles et cellulaires connaissent une augmentation du flux de signalisation principalement due aux applications fonctionnant sur des appareils mobiles connectés à ces réseaux. Le flux de signalisation dépasse de 30 à 50% celui des données mobiles et, peut avoir des effets néfastes sur les réseaux cellulaires s'il n'est pas géré de manière appropriée. Par ailleurs, la signalisation excessive peut encombrer le réseau, provoquant une congestion pouvant rendre le réseau indisponible, ou même vulnérable aux attaques. Les opérateurs sont donc amenés à faire face aux possibilités de pannes de réseau résultant de la signalisation excessive. Même si des tentatives ont été menées par les acteurs de l'industrie pour réduire ou mieux gérer le volume de trafic de signalisation, le problème persiste et continue de croître au fur et à mesure que de nouveaux appareils mobiles compatibles sont mis sur le marché. Dans cet article, nous proposons le concept de nœud d'assistance, un modèle pour réduire le volume de trafic de signalisation au niveau des réseaux cellulaires. Le modèle utilise des nœuds auxiliaires pour traiter les flux en fonction de la classification par les opérateurs de réseau. Les résultats de la simulation montrent qu'à travers les nœuds auxiliaires desservant d'autres nœuds du réseau et agissant dans le processus de relais, le volume de trafic éventuel au niveau des réseaux centraux est réduit. Ce modèle est rentable en ce qui concerne la mise en œuvre par opposition à l'introduction de nouveaux émetteurs-récepteurs radios. Cependant, une optimisation continue du réseau cellulaire est recommandée pour constamment suivre le volume de trafic de signalisation dans les réseaux cellulaires.

Mots clés: Réseaux cellulaires, modélisation, smartphones, signalisation, relais de signal

Introduction

Cellular phones have transformed the way in which people communicate. The capacity of cellular networks has increased over time, and more cellular devices are being released into the market. The volume of signaling traffic carried by cellular networks has been growing with the increase in subscriber base over the years (Shafiq *et al.*, 2011). Communication bandwidth for cellular networks has also increased and the number of active devices is now significantly more compared to some years back. The pace at which smartphone apps are developed and implemented is breathtaking (Gorbil *et al*., 2015). Consequently, there is an unprecedented surge in cellular network signaling volume attributed to the growth in popularity of smartphones and other data-enabled devices. With time, more sophisticated smartphones are being introduced into the market. This implies that the growth in signaling traffic volumes will continuously accelerate with technology and increase in the number of applications running on smartphones. In order to handle this huge traffic volume better, there is a need for cellular network providers to design and manage the networks accordingly.

Signaling traffic emanates from smartphone apps that create frequent background transmissions of small data sizes. Signal packet transmissions always occur even when the phone is assumed to be idle. During mass events, signaling volumes can be very high e.g., reaching beyond 250 signaling actions per base station per second (NSN, 2014). Use of smartphones generates two kinds of traffic (Gorbil *et al*., 2015); data traffic that carries information beneficial to the user and signaling traffic resulting from networks, devices, and applications interacting with each other. The way mobile apps are used is irregular and the launch of new apps can even crash the network. Signaling overload impacts all the users accessing the network. Some network elements that are not properly designed often experience reduced throughput because of the increased signaling requirements.

Different application categories contribute to signaling randomly and independently. For example, an Android-based smartphone creates two packet calls per hour due to the operating system without any applications. Traffic patterns often follow the distribution of usage patterns. The usage patterns can either be short rapid communication patterns, long duration and large volume patterns or fast and high data rate patterns. Short rapid communication patterns, correspond to very short, small quantities of data, generally less than 10 kB and sent/received in less than 60 seconds (Farrell *et al*., 2012) e.g., GPS updates, app interactions, and advertising updates. Long duration and large volume patterns entail large quantities of data (mostly downloads), usually up to several MBs over a long time (Farrell *et al*., 2012). The fast and high data rate patterns entail short bursts of high speed data (Farrell *et al*., 2012).

Efforts have been put in place though the signaling traffic problem still persists. For instance, approaches have been proposed for aggregating mobile app requests into fewer connection attempts (QUALCOMM, 2012). The requests are released to the network periodically when the connection gate is opened. During this period, pending requests are bundled into a batch and sent over the network. Other efforts include carrier aggregation and delay tolerant networks (Li *et al*., 2011). Delay tolerant networks benefit from the delay-tolerant nature of non-real time apps.

This paper proposes the Device in the Middle Model (DMM) to reduce the signaling traffic volume reaching cellular networks. The model uses helper nodes to service less critical traffic based on classification by network operators. Through the helper nodes servicing other nodes in the network and acting in the relay process, the eventual volume of traffic reaching the core networks is reduced. This model is cost effective in terms of implementation as opposed to introducing new radio network transceivers. The proposed model contributes to the existing approaches and mechanisms for handling signaling traffic.

The rest of this paper is structured as follows. Section 2 introduces the background and usefulness of traffic models. Section 3 presents the proposed helper node concept while Section 4 presents experiments, evaluation and the results. We review the related work in Section 5 and conclude in Section 6.

Overview and usefulness of traffic models. In this section we briefly introduce traffic models and their usefulness. Traffic models, mostly based on the telegraphic theory (Chen, 2007), are necessary for network operators to maintain quality of service (QoS). The theory applies mathematics to the measurement, modeling, and control of traffic in communication networks (Chen, 2007). Traffic modeling represents the behavior of users and traffic in the network. A good traffic model exhibits two distinct characteristics; accuracy and universality. Accuracy refers to the close fit between the model and actual traffic traces in statistical terms. At times, accuracy is also judged by the usefulness of the model to predict future behavior of traffic sources. Universality refers to the suitability of a model for a wide range of traffic sources. Ultimately, a traffic model is a mathematical approximation for real traffic behavior.

Measurements are useful and necessary for verifying the actual network performance, even though they do not provide the level of abstraction that makes traffic models useful. Traffic models can be used for hypothetical problem solving. The models can be used to generate synthetic traffic that can be injected into a network for measurement (Avallone *et al.*, 2004). Most traffic models apply mathematical modeling to explain the relationship between traffic performance and network capacity, traffic demand, and experimented performance. Such relations give an understanding on the necessary traffic controls and engineering techniques (Avallone *et al.*, 2004).

Traffic models are random processes that are often realized through traffic traces. The traces give insight regarding particular traffic sources. The models also give insight concerning all traffic sources of a particular type. Thus, these models are deemed necessary for proper optimization of network resources for a targeted QoS level. For example, packet traffic models are necessary for estimating bandwidth and buffer resources, especially for providing acceptable packet delays and packet loss probability. Also, knowledge of the average traffic rate is not sufficient. From the queuing theory, queue lengths increase with the variability of traffic. To be able to determine sufficient buffer sizes at nodes and link capacities, an understanding of traffic variability is necessary. Furthermore, traffic models can be used to verify network performance under specific traffic controls, and lastly, the models can be used for admission control.

Helper node concept. This section presents the helper node concept; the Device in the Middle Model (DMM) to reduce the signaling traffic volume reaching cellular networks. The Device in the Middle Model (DMM) introduces helper nodes between user equipment (UE) and the network. The helper nodes are used to service less critical traffic based on classification by network operators. Any traffic that is not able to be serviced by the helper nodes is passed to the network. In this way, the aggregate volume of signaling traffic reaching the network is reduced significantly.

In cellular network, almost every other aim is targeted towards improving the Quality of Service (QoS). QoS takes different characteristics including packet-delay, throughput, and error rate. Traffic demand is any form of traffic running over a network element. The traffic may be user-initiated through apps or system initiated through system services (processes). Signaling information is transmitted between nodes in the network. Thus, signaling can be equated to data transfers since packets are exchanged in both. This model considers background signaling traffic.

The background traffic consists of traffic from unattended phones with apps not in the active state (Zhang *et al.*, 2013). Open applications also cause traffic to rise since they require regular or intermittent communication with peer entities in the network. Key metrics considered for this modeling include the number of RRC state transitions, the probability of smartphone being active, and the distribution of the instantaneous number of active smartphones, i.e., the average number of active smartphones. A number of factors affect these metrics e.g., the size of the packet, inactive timer, and the distribution of the packet inter-arrival time. From previous studies (Zhang *et al.*, 2013), it is assumed that the network has a much higher pressure from the uplink signaling traffic than the downlink owing to the smaller channel capacity for the signaling traffic in the uplink than that in the downlink.

Key metrics are important for the background traffic that include the packet inter-arrival time and the packet size Cumulative Density Functions (CDFs). This implies that the background traffic can be modeled with a number of pseudo-random variables that represent the packet size, burst inter-arrival time, packet inter-arrival time within a burst, and the number of packets within a burst. Within 3G and 4G/LTE network cells, the background traffic for each smartphone is independent and random.

The DMM model allows the signals from nodes to be aggregated or serviced by helper nodes. In this model, either helper nodes send signals to the network and advertise it to nodes in the neighborhood, or the helper nodes participate in servicing other nodes in the network. If we consider the case for helper nodes advertising signals to the neighborhood, then when permission to transmit is granted, other nodes in the neighborhood also transmit during this transmission window. This way, only a few nodes send signals to the network and the other nodes opportunistically take advantage. Aggregating the signal and data transfers whenever possible can significantly reduce the total energy drain of apps and the resulting signaling volume (Ding *et al*., 2013). To concretely demonstrate the DMM model we consider different use scenarios:

Definition of key symbols used

φ to be the number of state transitions.

μ_h to be the rate of arrival of helper node packets.

ω_t to be the inactive timer.

λ_t to be the packet inter-arrival time.

Scenario 1. If we consider a network with only one helper node (H_n) and an infinite number of smartphones in the *active* state and a packet arrives within the inactive timer (ω_t), will remain in the *active* state without transition. This implies that if, state transition () will not occur. Also, if the packet arrives after, the smartphone will first switch to $inactive$ state and then back to $active$ state, meaning a state transition will occur. This implies that if, will increase by one, the average number of transitions is given by;

Scenario 2. If we consider the probability of a helper node being in the *active* state, then we need to analyze the time the device is *active* ().is influenced by ,, and the CDF of the . We assume to be linearly proportional to. If we assume the helper node to be in *active* state, and if , a new packet will arrive within . This indicates that the helper node will stay *active* without state transition. determines the time duration the helper node remains in the *active* state. However, if , the new packet will arrive when the device is *inactive*. Thus, determines the time of the helper node being \$active\$. Hence, the mean time of a helper node being in *active* state is given by;

$$\bar{\phi}_{ha} = \alpha\theta_t\mu_h$$

Where:

$$\alpha = \sum_i (\lambda_t Pr\{i\}) + (\lambda_t Pr\{\lambda_t > \omega_t\})$$

$$i = \lambda_t \leq \omega_t$$

And the probability of the helper node being *active* is given by;

$$Pr(ha) = \frac{\bar{\phi}_{ha}}{\theta_t} = \alpha\mu_h$$

Scenario 3. The instantaneous number of helper nodes in the *active* state (\$N_{ha}\$) is useful for determining the signaling traffic hitting the network. This number is influenced by the number of helper nodes in the network () and Pr (ha). The mean number of \$active\$ helper nodes is given by;

$$\bar{N}_{ha} = N_h Pr(ha) = \alpha N_h \mu_h$$

Given that we know the average number of helper nodes in the network and we assume the total average number of other nodes in the network to be \$M\$, then the total number of devices in the network is given by . If we let the signaling traffic to be *S*, then the average signaling traffic reduction is given by;

$$\bar{S} = \frac{M}{\bar{N}_{ha} + M}$$

How the Model works. In the current scenario, all signaling traffic is treated as high priority. Therefore, all the traffic is relayed to the network for servicing as depicted in Figure 1. However, close examination of the signaling traffic, reveals that some of the traffic can be delayed without causing any adverse effects to the user experience. Therefore, we argue that the signaling traffic can be classified into two categories; one category for true high priority traffic (THPT) and another category for false high priority traffic (FHPT). The false high priority traffic is delay tolerant e.g., traffic from social networking apps whose main intent is to probe the network for status updates and postings. This kind of traffic can afford to be delayed. A typical true high priority traffic is a phone call. Such traffic cannot wait and has to receive immediate service from the network.

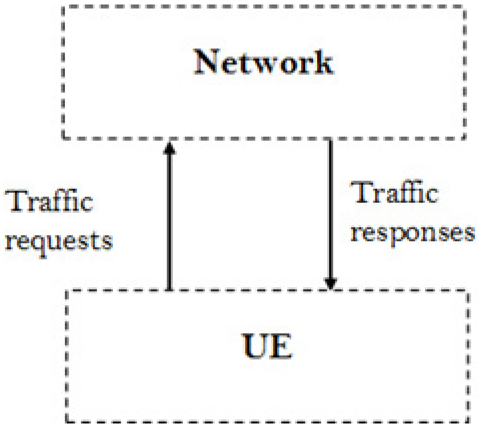

Figure 1. Current network relay

From Figure 2, the helper node sits between the UE and network. The helper nodes service the FHPT traffic from the UE. THPT from the UE goes directly to the network. However, if the helper node does not have responses to some of the FHPT, then that particular traffic requests are sent directly to the network.

False high priority traffic (FHPT) is delay tolerant e.g., traffic from social networking apps on mobile devices. On the other hand, true high priority traffic (THPT) is not delay tolerant and once the UEs send this kind of traffic to the network, it has to be serviced. However, if resources are not available to service this kind of traffic, then it is either blocked or dropped. The DMM model is ideal for FHPT since the servicing of this kind of traffic can be done through other nodes participating in the relay process. Consequently, we conclude that this model helps in reducing the total traffic reaching the cellular networks by serving the FHPT. The total signaling traffic in the network is a combination of THPT and FHPT. Therefore,

$$S = THPT + FHPT$$

And using the DMM model, the traffic reaching the network is given by;

$$S = THPT + FHPT_{ren}$$

where $FHPT_{ren}$ is the fraction of FHPT not serviced by the helper nodes. Also,

$$FHPT = FHPT_{serviced} + FHPT_{ren}$$

Where $FHPT_{serviced}$ is FHPT serviced by the helper nodes. Therefore, the model reduces the volume of signaling traffic reaching the cellular networks by;

$$\Psi_{red} = \frac{FHPT_{serviced}}{S}$$

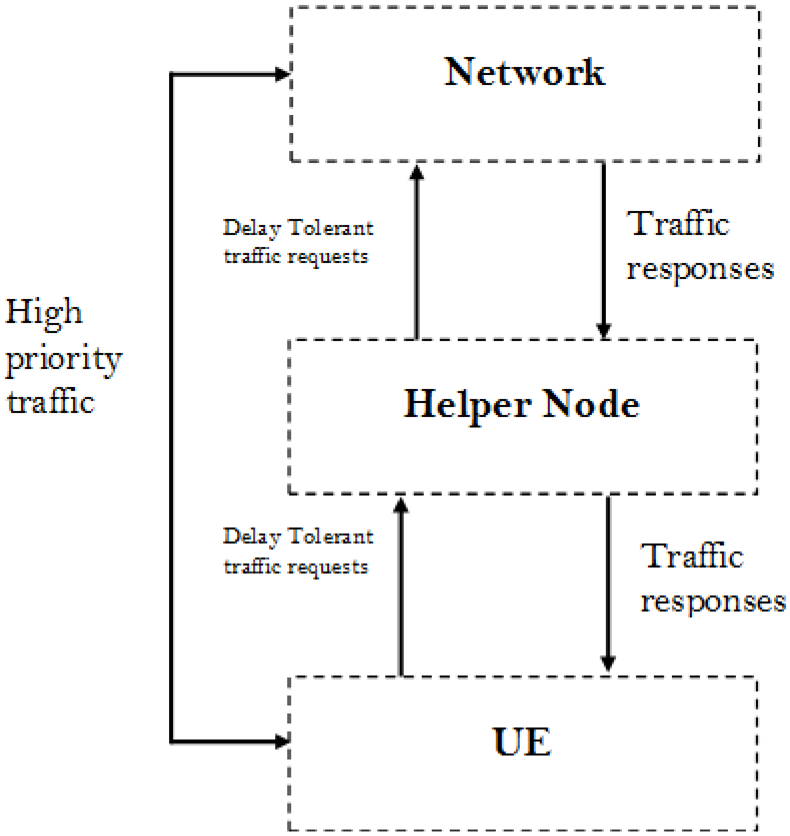

Figure 2. Device in the middle model

Where Ψ_{red} is the fraction of the total traffic serviced by the helper nodes.

To avoid too much signaling traffic reaching the network, especially during crowded event, the helper nodes can be fully configured to handle all traffic. In this case, all the network capabilities are transferred to the helper nodes, though, this requires having in place helper nodes that can fully handle the network capabilities.

Selecting helper nodes. The criteria for selecting helper nodes is dependent on policies put in place by network operators. However, unique options for selecting helper nodes inherently stand out.

Option 1. Consider a network operator with devices randomly distributed in the network. The operator may decide to select a subset of these devices to act as helper nodes. This scenario is applicable in densely and sparsely populated locations. In sparsely populated locations, the operator may decide to strategically position helper nodes within the network.

Option 2. Consider a population accessing the cellular network with mobile devices. The operator may give incentives to lure some mobile users to permit their devices to be used as helper nodes.

Option 3. There are some instances when users have common interests. In this case, the network operator can deliver information to a small fraction of the users who can then further disseminate the information to others. However, this requires network operators to have appropriate and effective incentive schemes to stimulate users' participation in traffic offloading.

Model evaluation and results

Experiment setup. Simulations were carried out to determine the level of signaling hitting cellular networks. The simulations were modified to include the device in the middle scenario to service some of the signaling traffic generated. OMNeT++ (Varga, 2010; Dräxler *et al*., 2012; 12;Virdis *et al*., 2014) was used for the simulations because it is used widely in scientific simulations. In order to get the performance of our proposed model (DMM), an environment with numerous mobile devices was considered. The simulated network consisted of two (2) network transceivers each with three (3) associated helper nodes. Each helper node had eight (8) devices attached to it. In the simulation experiment, six (6) helper nodes were placed between forty eight (48) end user devices and two (2) base stations. The end user devices request for signal service from the helper nodes. If the helper nodes are unable to service the UE requests, they transfer the request to the network. The network sends the service request responses to the helper nodes which serves the UE. High priority traffic is serviced by the network.

Results

Figure 3 shows the simulated DMM model results. The graph depicts a decay trend. This implies that with the introduction of helper nodes to sit in between the UE and the network, some of the signaling requests from the UE are serviced before reaching the network. This translates to a reduced volume of signaling traffic reaching the network.

Figures 3 and 4 show a comparison between the desirable signaling traffic trends in the network and the results for the simulated DMM model in reducing the volume of signaling traffic reaching the network. Both graphs depict a decay trend. This implies that the DMM model if applied in a real network environment, can actually serve to reduce the volume of signaling traffic significantly.

The simulation results for the simulated DMM model are as indicated in Figure 3. The signaling traffic volume (y axis) is expressed as a function of time (x axis). The traffic ranges between high and low peaks, though, the linear, exponential, and logarithmic distributions show a decay trend. This means that with the introduction of helper nodes, some of the traffic is serviced without necessarily reaching the cellular networks. Consequently, the signaling traffic volume reaching the network reduces significantly. Some of the helper nodes can fully be configured to handle all traffic, especially during events where there is the likelihood of having a higher concentration of mobile devices.

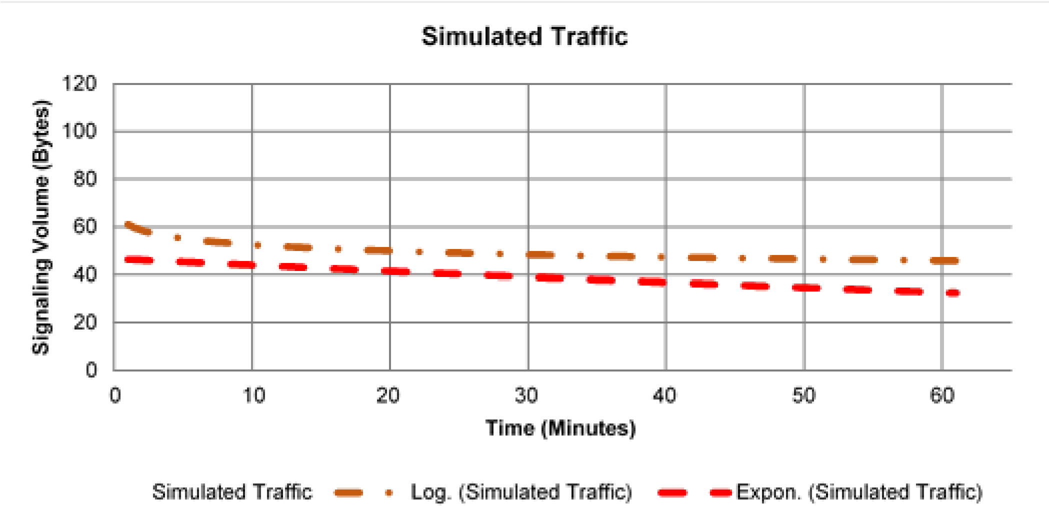

Figure 3. Simulated signaling with helper nodes

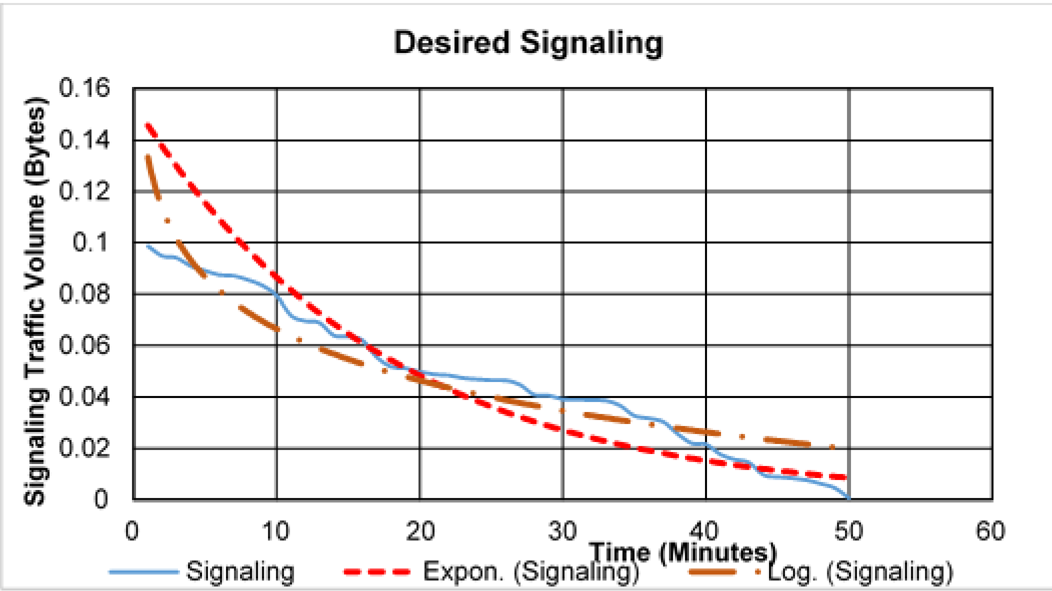

Figure 4. Desirable network signaling

Effect of mobile location on the Model. The location of the mobile in relation to the serving base station has an effect on the level of signaling. Mobiles at the fringe of a cell tend to receive low quality signal levels. The implication of this low signal levels is that either the network or the mobile begin to initiate handover processes to determine the nearest base station with the best signal quality. This results in high volumes of signaling traffic. Thus, the model can perform well when combined with other schemes for increasing system capacity e.g., cell sectoring, cell splitting, and micro-zoning.

Effect of Model parameters on performance. The experimental results show a good overall performance of the model in terms of reducing the volume of signaling traffic reaching the network. The serving node is closer to the UE. However, if the serving node fails, then the signal load has to reach the network for servicing. Also, in the event that the serving node fails, then it takes longer for signals to reach the network. The average number of hops will always be reduced by a fraction of the distance between the UE and the network. This means that if the total distance between the UE and the network is *d*, and the number of signal hops required is *h*, then the average number of signal hops is *h/d*. A reduction of the number of signal hops by a fraction of the distance, reduces the average distance the signal has to travel to reach the service point and back. Also, the time delay factor is reduced by a factor of the number of hops reduced to reach the service center and back. Though, when operating under optimally ideal conditions, this model reduces the level of signaling volume reaching cellular networks significantly. Operators can assume the shortfalls with regular optimizations of the cellular networks. Also, allowing other devices to participate in signal propagation and servicing saves on extra bandwidth assigned to the base stations. The redeemed bandwidth can be re-farmed.

Related work. Other approaches have been proposed to handle and manage network traffic. For instance, the network socket request manager (NSRM) (QUALCOMM, 2012) gates mobile app requests on smartphones when operating in background mode. Multiple app connection attempts are aggregated into fewer connection attempts. The connection gate is opened immediately upon the user turning their screen on, or periodically based on a timer. All pending requests are bundled into a batch and sent over the network once the gate is opened. This reduces the connection attempts, the signaling load on the network and the amount of time the device spends in the connected state. This technique also reduces the standby power consumed by the mobile device. The gating mechanism ensures no delays to app requests that can negatively impact the app behavior or user perception of the application performance. The NSRM delays asynchronous requests from multiple apps and bundles them together. The delaying is accomplished by using timers and counters that record the number of intercepted requests. If the mobile device goes into active mode, pending requests are executed.

Carrier aggregation is another approach through which operators increase capacity. Radio spectrum is a limited resource that requires large capital expenditure to acquire. For mobile apps, timers have been introduced to help with chatty application behavior such that the apps spent the least amount of time in the connected state. Most of the mobile app requests are initiated from within the device through a pull mechanism. Pull requests results into downlink data, majorly for updates e.g., news feed, weather syndicates etc. Other apps like email are notified by the push mechanism. In the push mechanism, data from the server is periodically pushed.

Delay tolerant networks (DTNs) approach has also been used to migrate cellular data traffic (Li *et al.*, 2011). The approach benefits from the delay-tolerant nature of non-real-time apps such that service providers can delay and shift transmissions to DTNs. Since some users have common interests, network operators can deliver information to a small fraction of users who can disseminate further through DTNs. However, operators must have proper and effective incentive schemes to entice users to participate in the data offloading.

Some mathematical frameworks have been proposed for mobile data offloading as well. Li *et al*. (2011) proposed a mathematical architecture for DTN-based mobile traffic offloading. The architecture takes into consideration a network with heterogeneous users. The consideration takes into account a number of factors including data preference and privacy intentions, delay sensitivity and size for the offloaded data, and offloading helper having limited storage. The architecture is formulated under multiple linear constraints as an optimal DTN offloading considering the heterogeneity of traffic, users, and limited storage as a problem of sub-modular function maximization.

Conclusion and future work

The experimental results show a good overall performance of the proposed model in terms of reducing the volume of signaling traffic reaching the network. The serving node is closer to the UE. However, if the serving node fails, then the signal load has to reach the network for servicing. Also, in the event that the serving node fails, then it takes longer for signals to reach the network.

The model performance was evaluated based on simulations. Future work will entail testing the model on some sample live networks. Also, different mobile operating systems are bundled with services that probe the cellular networks periodically. For optimal design and development of mobile operating systems (OSs) that are sensitive to signaling, it is worth exploring the underlying software architecture designs to extend signaling traffic control to the mobile OSs.

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